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Research Article

Precise roadkill environmental factors identification for sustainable planning and design through spatial and temporal modelling

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Abstract

Roads are major drivers of habitat fragmentation and amphibian mortality. Effective mitigation requires understanding species-specific, temporal, and multiscale environmental drivers, yet such integrated analyses are uncommon. Additionally, amphibian species in our region are understudied, and fine-scale roadkill drivers remain globally underexplored. This study aims to identify precise roadkill predictors for these species by integrating these approaches and to develop a framework for translating the findings into context-specific ecological planning and design. We combined standardized surveys and citizen science roadkill data for five anuran species in a Taiwanese biodiversity hotspot and analyzed them at three levels: multispecies, single-species, and single-species temporal subsets. We employed a dual Random Forest and Logistic Regression consensus approach, assessing a comprehensive set of predictors, including fine-scale roadside features, across multiple spatial scales (25–250 m) with an innovative uphill–downhill buffer design. We identified 24 robust consensus predictors, with habitat-related (e.g., water proximity, forest cover) and road-related fine-scale factors (e.g., streetlights, retaining walls, drainage channels) being equally important. Species-specific and temporal models (AUC up to 0.851) significantly outperformed the multispecies model, showing that predictor relevance and the scale of effect shift seasonally at inter- and intra-specific levels, particularly during breeding migrations. Our findings underscore that generalized approaches are insufficient for effective roadkill mitigation and highlight the need for context-specific, evidence-based ecological planning and design. The study provides a transferable framework that links ecological traits and predictor relevance to actionable, multi-stage planning, design, and operational management guidelines. This approach shows how integrating ecological precision with planning relevance can enhance biodiversity conservation for sustainable development.

Key words: Ecological modelling, hotspots identification, multiscale environmental analysis, road ecology, roadkill patterns identification, species distribution modeling, wildlife–vehicle collisions

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Introduction

Roads are major drivers of habitat fragmentation, wildlife mortality, and biodiversity loss worldwide (van der Ree et al. 2015). Amphibians are disproportionately affected because they depend on both terrestrial and aquatic habitats,

have limited mobility, and undertake explosive breeding migrations that force mass road crossings (Beebee 2013; Groff et al. 2017; Heigl et al. 2017; Ascensão et al. 2021). These traits cause recurrent, large-scale mortality events that accelerate population declines, making their roadkill a global conservation concern (Matos et al. 2012; Pinto et al. 2023).

Amphibian roadkill is influenced by environmental factors that affect animal movement and exposure to vehicular traffic (Jones et al. 2024), and such influences are frequently identified as species-specific and temporally dynamic. Proximity to water resources is widely recognized as a critical determinant of amphibian roadkill (Pinto et al. 2023; Jones et al. 2024), yet the specific hydrological features influencing this are highly species dependent (Coelho et al. 2012; Matos et al. 2012). Pinto et al. (2023) demonstrated that while the Iberian spadefoot toad (*Pelobates cultripes*) and the Iberian ribbed newt (*Pleurodeles waltl*) experienced higher mortality near mapped waterbodies, the Natterjack toad (*Epidalea calamita*) exhibited higher mortality at greater distances, which is likely due to its reliance on unmapped ephemeral ponds. Similarly, Coelho et al. (2012) observed that while anuran roadkill aggregations were generally associated with natural waterbodies, mortality of *Leptodactylus latrans* was principally driven by the presence of roadside ditches. Landscape composition, including forest cover, agricultural land, and residential development, affects habitat suitability, dispersal routes, and the probability of encountering roads, which are also important amphibian roadkill drivers (Coelho et al. 2012; Heigl et al. 2017). These influences also vary among species and their life cycles. Cosentino et al. (2014) discovered that the effects of upland habitat composition (forest and developed land) on species distributions differed. Additionally, Groff et al. (2017) found that wood frogs selected different habitat features and exhibited different movement patterns during spring migration compared to their foraging period.

The species and temporal dynamic behaviors resulted in various movement-related spatial ranges, necessitating a multiscale approach for roadkill patterns. Bailey and Muths (2019) argue that amphibian movement occurs at multiple organizational levels—individual (local movement), population (migration), and metapopulation (dispersal)each operating at different spatial and temporal scales. Furthermore, movement distances through the anthropogenic matrix exhibit high interspecific variability, ranging from 0 to over 1500 meters, driven by specific ecological requirements (Cassimiro et al. 2023). Consequently, the “scale of effect”—the spatial extent at which species perceive and interact with the landscape—is intrinsically linked to species traits and mobility (Matutini et al. 2021). Relying on a single spatial scale may therefore fail to capture the “statistical signal” of species-environment relationships, particularly for generalist species that utilize broader habitat ranges (Matutini et al. 2021). Empirical evidence also supports this necessity, as Jones et al. (2024) demonstrated that analyzing data at multiple scales (e.g., 50 m versus 250 m) aids in identifying important variations among species that might otherwise be masked in single-scale analyses (Jones et al. 2024).

Effective mitigation requires understanding these species and life cycle dependent variations (Bailey and Muths 2019; Helldin and Petrovan 2019; Ottburg and van der Grift 2019; Matutini et al. 2021), as such knowledge remains scarce, hindering prediction accuracy and conservation outcomes (Petrovan

and Schmidt 2019; Cassimiro et al. 2023). Species-specific and temporal approaches can reveal finer ecological drivers and ensure mitigation relevance (Coelho et al. 2012; Heigl et al. 2017). Identifying roadkill drivers across spatial scales can guide more precise and effective conservation actions. Despite recognition of these needs, integrated approaches combining species-specific, temporal, and multiscale analyses remain uncommon (Coelho et al. 2012; Matos et al. 2012; Heigl et al. 2017). Most studies focus on well-known taxa or generalized predictors, leaving gaps for less-studied species and fine-scale features. Bridging these gaps is critical for developing mitigation strategies that are both ecologically sound and transferable to practical mitigation practices.

Here, we address these gaps through a case study on a country road located in Taiwan's Sanxia District, a biodiversity hotspot rich in amphibians. The study road exemplifies a common fragmentation scenario, separating forested uplands from lowland waterbodies. Such configurations occur globally—in Europe (Matos et al. 2012), North America (Cosentino et al. 2014), South America, and Australia (Hamer 2016)—underscoring the wider applicability of our findings., We analyzed five understudied amphibian species using standardized roadkill surveys together with citizen-science data. We incorporated a species-level approach alongside multispecies and temporal models to ensure a holistic understanding of roadkill risk. Beyond common predictors such as waterbodies, topography, and land cover, we conducted detailed environmental surveys, including uphill–downhill delineation, across both local and broader scales to enhance predictor relevance. We tested underexplored roadside features including streetlights, verge cover, junction design, traffic barriers, retaining walls, and drainage structures. Predictor selection was relied on statistical preselection followed by a dual Random Forest (RF)–Logistic Regression (LR) approach to ensure reliability. To operationalize our findings, the multiscale predictor framework facilitates translating species trait-based features into practical planning and design practice, combining broad habitat variables with fine-scale road attributes. By linking ecological traits, predictor relevance, and practical mitigation feasibility, we aimed to (i) build a knowledge base that delivers actionable insights into roadkill–environment relationships, and (ii) provide a framework for translating these findings into strategic interventions for both existing and new developments. Ultimately, this study demonstrates how combining ecological precision with planning and design relevance can enhance biodiversity conservation and sustainable development.

Materials and methods

Study area

The study road is situated in the mountainous region of Sanxia District, New Taipei City, along part of the North 114/115 country road in northern Taiwan, starting from Baxian Bridge where it crosses Ruizi Creek and ending at the parking area of the entrance to Manyueyuan National Forest Recreation Area (Fig. 1). It serves local traffic and provides the main access to the recreation area. The road runs north-south, ascending from 240 m to 360 m over 3.2 km with an average slope of 3.75%. It parallels the Ruizi Creek on its eastern side and crosses seven tributary streams, while the western side is bordered by steep forested

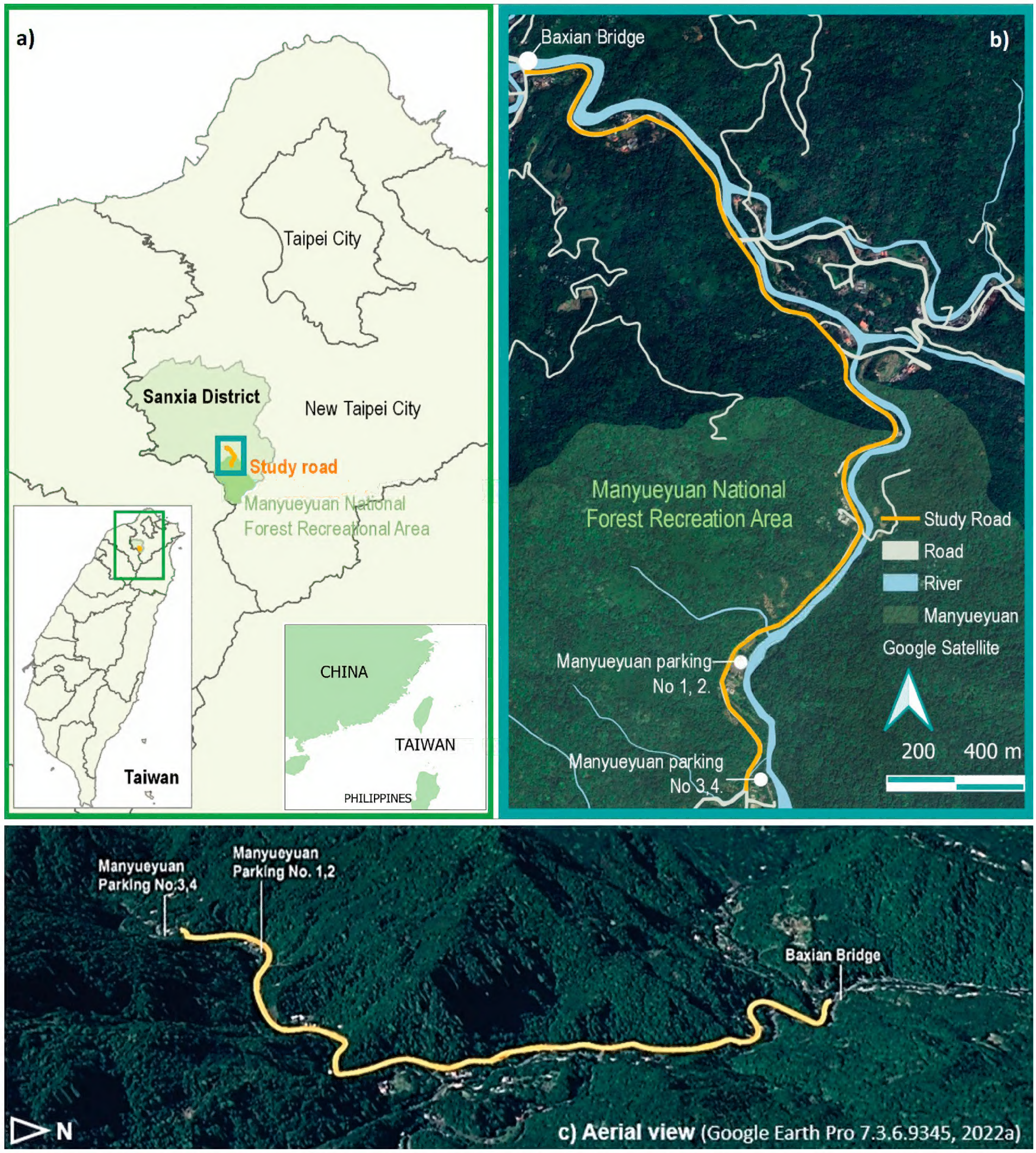

Figure 1. Study site maps. **a.** Site location; **b.** Detailed site map showing the study road running parallel to the river and bisecting the landscape; **c.** Aerial view of the study site illustrating the steep, mountainous terrain with the river valley and road located at the foot of the slopes.

hills. The surrounding landscape consists mainly of broadleaf forest, with patches of bamboo forest, orchards, crops, and scattered residences (Fig. 2).

Taiwan currently hosts 43 recognized anuran species (TBN 2025), of which 22 have been recorded in the study region—one of the country's highest amphibian diversity concentrations (Yang et al. 2022). This setting, where a valley road bisects upland forest and lowland aquatic habitats, represents a typical configuration of habitat fragmentation, making the site

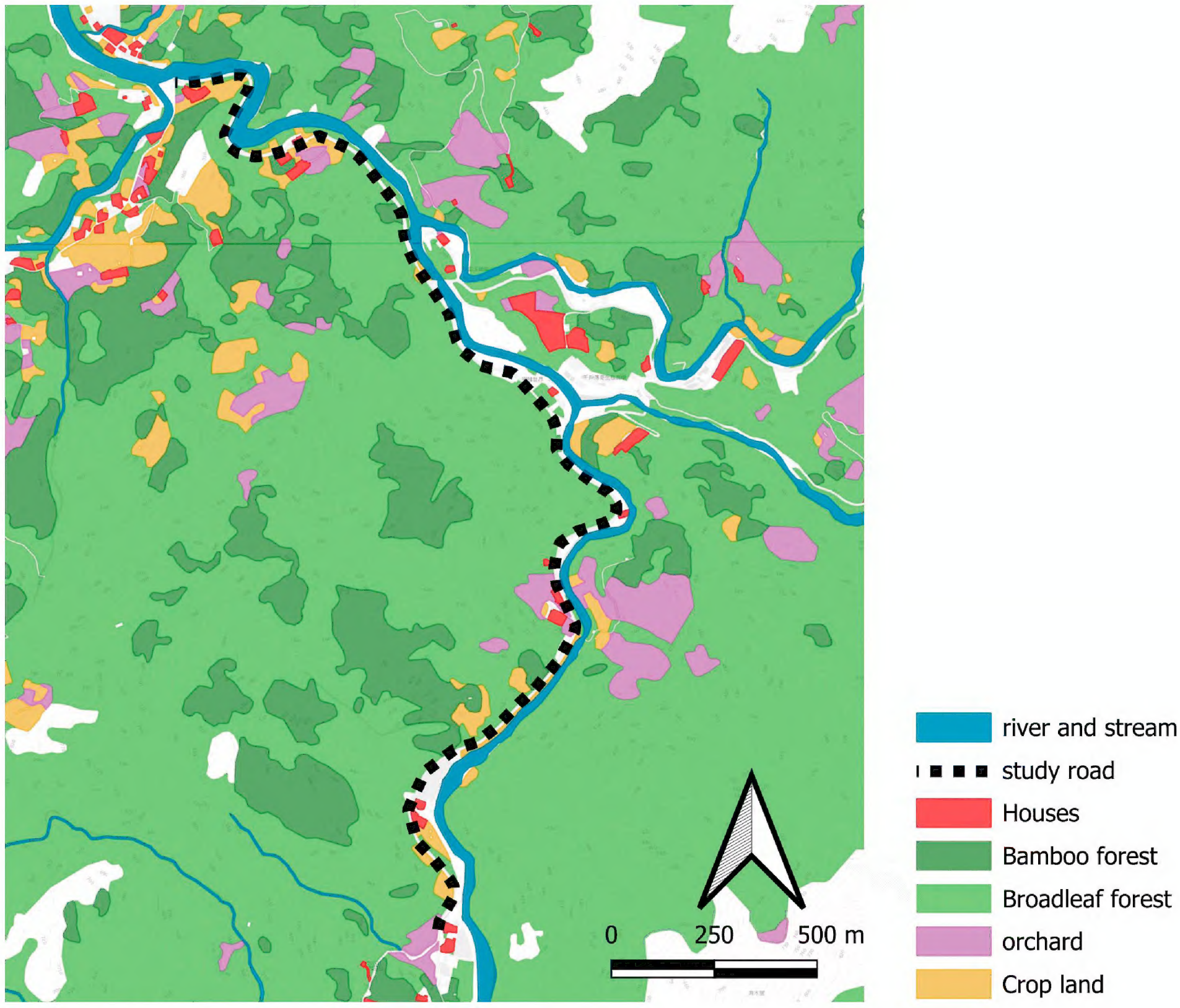

Figure 2. Maps showing the spatial arrangement of surrounding land uses at the study site (NLSMC 2019).

ecologically significant within Taiwan and broadly representative of road–wildlife conflicts in comparable landscapes worldwide (Matos et al. 2012; Cosentino et al. 2014; Hamer 2016).

Roadkill data

Standardized amphibian roadkill carcasses were surveyed along the entire length of the study road approximately every two weeks from April 2018 to September 2019, resulting in a total of 33 surveys. Surveys were conducted using motorbikes (speed ≤ 10 km/h) and on foot, with 1–2 observers per survey. The collected data underwent a filtering process: points located more than 75 meters away from the roads were removed due to imprecise GPS records or accidental observer recording errors, as the survey was strictly on the road; only records identified as belonging to the Class Amphibia were retained for further analysis. The survey and data filtering protocol was previously reported in Karanasios et al. (2021). As a result, a total of 234 amphibian roadkill records were retained from the survey data, all belonging to Order Anura, of which 124 (53%) were identified to the species level (see Suppl. material 1: table S1).

Rana sauteri is a recognized vulnerable species (IUCN 2020d) in Taiwan. Records of *R. sauteri* mass mortality roadkill events were documented in a citizen science database of the Taiwan Roadkill Observation Network (TaiRON) (Lin 2022) between late October and mid-November 2017, reporting 118 fatalities at six locations on our study road (see Suppl. material 1: fig. S1). As no such mass mortality events of *R. sauteri* were observed during our survey period (4 records of 4 fatalities in our survey data), we included these records in our study for two reasons: first, they provide ecologically relevant and critical information on species-specific migration movements and subsequent mortality, which could have significant population consequences (Farias et al. 2022). Second, these events occurred shortly before our survey period on our study road, allowing for analysis in the same environmental context.

As there was no earlier pilot study on the study road to inform which species should be prioritized, target species were selected based on the requirements of the modeling procedure (Norberg et al. 2019). During the data exploration stage, small sample size was the main limitation for further analysis (see Suppl. material 1: table S1). We examined the species sample sizes and determined whether they could be divided into meaningful test sets for cross-validation during model training (Hastie et al. 2009; Kapoor et al. 2024). We also assessed whether these samples exhibited a statistically significant difference when compared to the pseudo-absence samples during the predictor preselection process (see the following sections on pseudo-absence data and predictor preselection). Five target species were selected after these examinations, which were *Bufo bankorensis*, *Buergeria robusta*, *Hylarana latouchii*, and *Odorrana swinhoana* from the survey data, *Rana sauteri* from the citizen science data. We excluded most species due to their small sample sizes, except for *Hylarana guentheri*, which was excluded because it showed no significant differences from the pseudo-absence samples.

Among the five selected target species, only *B. robusta* had clearly reported May–June migrations according to local frog-rescue volunteers (Frog in Sanshia 2024). Their observations indicate breeding-related seasonal movements and a high frequency of roadkill, with individuals moving toward adjacent rivers in May and returning from the river in June (Chen 2019; Let's RE 2020). To examine the temporal dynamics of *B. robusta* roadkill, we divided the data into four temporal subsets based on these migration periods and the monthly availability of records (Suppl. material 1: fig. S1). Because no roadkill was detected from November to February, we classified the remaining records into a pre-migration period (April, n = 8), the peak migration to the river (May, n = 17), the return peak (June, n = 11), and a post-migration period (July, n = 5; August, n = 3; October, n = 1). Post-migration records were aggregated to ensure adequate sample size, similar to Lin et al. (2019). Although this temporal division is not formally documented, it aligns with local observations and provides a practical framework for assessing seasonal variation in roadkill predictors. For each subset, we assessed sample sizes and tested whether they differed significantly from pseudo-absence samples to confirm inclusion in the study.

Finally, roadkill data were grouped into 10 roadkill samples of three sample types: one multispecies sample (multispecies, n = 234, including all amphibian roadkill records from survey data, comprising 124 records of 14 species and 110 records not identified to species level); five single-species

samples (*B. bankorensis*, n = 19; *B. robusta*, n = 45; *H. latouchii*, n = 13; *O. swinhoana*, n = 25; *R. sauteri*, n = 6); and four temporal single-species samples for *B. robusta* (*B. robusta* April, n = 8; *B. robusta* May, n = 17; *B. robusta* June, n = 11; *B. robusta* July–October, n = 9).

Pseudo-absence data

To generate pseudo-absence data, we first placed 2,340 random points on the centerline along the entire 3.2 km study road. We then drew 1,000 bootstrap random samples (with replacement), each containing 234 points (a 1:1 ratio with the multispecies sample) from this pool. The initial pool of 2,340 points served to provide comprehensive information on the available environment along the road, while the bootstrap selection of 234 points was used to down-sample the majority class to address class imbalance (Valavi et al. 2021). All roadkill samples were analyzed against these 1,000 random samples; this bootstrapping procedure ensured the robustness of predictor preselection and model fitting (Aranda-Michel et al. 2022).

Environmental predictors

Predictors are organized into two categories: habitat-related and road-related (Table 1; a comprehensive list detailing each individual predictor is provided in the Suppl. material 1: table S2). Habitat-related predictors include variables related to amphibian habitat requirements, such as water, topography, and landscape features. Road-related predictors include features directly adjacent to the road, considering not only habitat quality but also potential barriers or other factors that may trigger amphibian behavioral reactions. Each predictor was examined and processed using a multiscale approach to explore its effective scale, which refers to the spatial distances at which predictors influence amphibian roadkill probability.

Table 1. Environmental predictors summarized by category.

Predictor	Description
Habitat-related Predictors	
Water Features	Measures proximity to and characteristics of water features available. Examples: Euclidean distance to nearest stream (D_StreamUp), area of river in buffer (River), Strahler stream order (Stramax). These predictors were examined in distance and multiple spatial scales.
Topography	Describes the physical landform, which influences microclimate, hydrology, and movement pathways. Examples: Elevation, slope (Slpmean), aspect (Aspect_N, Aspect_S). These predictors were examined in local and multiple spatial scales.
Landscape Features	Quantifies the composition of the surrounding landscape, indicating habitat quality and availability. Examples: Area of broadleaf forest (BLeafF), area of cropland (Crop), area of residential land (House). These predictors were examined in multiple spatial scales.
Road-related Predictors	
Streetlights	Count of streetlights.
Roadside Land Uses – Land Covers	Describes human activities and land cover immediately adjacent to the road. Examples: Length of farming land (RS_Farm), length of building walls (RS_Wall), presence of bus stops/shops (RS_Facility). Fine-scale habitat features offering cover, foraging opportunities, or moisture. Examples: Length of unmanaged grass (RS_LongGr), leaf litter accumulation (RS_Bottom), open paved ground (RS_OpenGP).
Vertical Structures	Man-made barriers along the road that can impede or funnel animal movement. Examples: Length of Jersey barriers (RS_JerseyB), W-Beam guardrails (RS_WBeam), retaining walls (RS_CRWH).
Open Drainage Channels	Drainage channels that can act as habitat or traps, depending on their condition. Examples: Length of clear drain (RS_OpDrain), drain with leaf litter (RS_OpDrainB), waterlogged drain (RS_OpDrainW).

Extracting predictor values using multiscale buffers

We extracted predictors within buffer zones of 25, 50, 100, 150, 200, and 250 m around each sample point. These radii capture ecological scales relevant to the study species and reflect the spatial limits of the river valley. The maximum 250 m buffer ensured analyses remained within valley boundaries, while the 25 m buffer represented immediate roadside effects consistent with the limited mobility of anurans (Beebee 2013). Intermediate buffers, increased by 50 meters, allowed a multiscale analysis of broader habitat influences such as land use and water features, following best practices in species distribution modeling (Elith and Leathwick 2009), balancing ecological relevance with spatial accuracy.

As the road runs at the foot of steep, forested hills with the Ruizi Creek flowing alongside it, environmental conditions consistently differ between the uphill and downhill sides. To account for this, we kept local scale using a 25 m radius buffer counting both sides of the road, and we divided all multiscale buffers into uphill and downhill sections based on the road centerline (Suppl. material 1: fig. S2). This design enables us to evaluate roadkill drivers from each side of the road, under the condition that the presence of an important water feature was constantly on one particular side (Jones et al. 2024).

Habitat-related predictors

Water features included distance to different water sources available along the road, including distance to the Ruizi Creek, uphill streams, stream crossing points, farm drains, culverts and running water sources on the road. The presence of Ruizi creek was also examined as an area in multiscale buffers. Stream network was included using Strahler order (Strahler 1957; Kuemmerlen et al. 2019) within multiscale buffers to capture the influence of both larger and smaller tributary creeks.

For topographic features, we included elevation, aspect and slope. Terrain aspect was included as a categorical predictor because slope orientation affects microclimate and amphibian behavior on roads (Heigl et al. 2017; Morelli et al. 2023). Elevation and aspect were extracted directly at sample points, while slope was summarized as mean values within multiscale buffers.

Landscape characteristics surrounding the road were also assessed, as both natural and anthropogenic land uses can strongly influence amphibian distributions (Gunson et al. 2011; Matos et al. 2012; Pinto et al. 2023). We therefore quantified broadleaf and bamboo forests—the two dominant forest types in the area—as well as crops, orchards, and housing within the multiscale buffers.

Road-related predictors

Most roadkill studies emphasize traffic volume and broad habitat types. However, for amphibians, whose mortality is significantly influenced by microhabitat and immediate roadside conditions, it is essential to carefully select ecologically relevant predictors that align with the species and the scale of the process being investigated. To improve predictive accuracy and provide the ecological context needed for targeted interventions, we expanded the variables set to include fine-scale local road features.

Previous research highlights the influence of various roadside features, including streetlight spectra (Van Grunsven et al. 2017), surface materials (Gunson et al. 2011; Pinto et al. 2023), roadside vegetation (Santos et al. 2007), understory cover (Gunson et al. 2011; Coelho et al. 2012; Kouris et al. 2024), and drainage ditches (Coelho et al. 2012; Matos et al. 2012). These elements can act as attractants or ecological traps (e.g., ditches) and can alter movement patterns (e.g., vertical structures). Building on this foundation, we broadened our scope to evaluate a wider range of underexplored roadside features along our study road (see Table 1, Suppl. material 1: table S2).

Streetlights were evaluated in both local and multiscale buffers. Roadside land uses included features adjacent to the road, such as parking areas, traffic junctions, vegetation strips, pavements, road verges, and the walls of roadside buildings. Additionally, we documented vertical structures, including Jersey barriers, W-beam guardrails, and retaining walls of various materials and heights. Finally, we assessed drainage channels, focusing on their condition (clear, vegetated, leaf-littered, or waterlogged), as these qualitative differences may influence amphibian movement and mortality. These variables aim to improve predictions and directly inform effective mitigation design.

Spatial data for land use and topography were obtained from the National Land Surveying and Mapping Center of Taiwan (NLSMC 2019). Topographic parameters and Strahler order were derived from a 20 m digital terrain model (DLA 2020). Streetlight data were retrieved from Taiwan's open data platform (PWD 2019). Roadside land uses, vertical structures, and drainage channels were mapped during GPS-based field surveys conducted in parallel with roadkill monitoring (March 2018–September 2019), with additional detailed surveys in November 2019, July 2020, and April 2022. All spatial analyses were performed in QGIS 3.34 (QGIS 2023).

Predictor preselection

For each analyzed sample, we performed predictor preselection to exclude potentially noisy predictors and reduce dimensionality for subsequent modeling. All predictors for each roadkill sample respectively underwent univariate screening tests compared with the 1,000 bootstrap random samples based on variable type: continuous predictors were evaluated using both the Mann–Whitney U test and univariate logistic regression, while categorical predictors were assessed with the chi-square test (Aranda-Michel et al. 2022). The Harmonic Mean p-value method (HMP) (Wilson 2019) was used to aggregate test results, and predictors that remained statistically significant ($p < 0.05$) were retained for subsequent modeling. To avoid redundancy, Spearman's correlation coefficient ($|r| > 0.7$) was applied to remove highly correlated predictors, which can bias variable importance estimation; predictors with stronger HMP support were retained. The variance inflation factors (VIF) for the remaining predictors were also examined, and we kept no predictor's VIF exceeding 10 for each sample (Heigl et al. 2017). The remaining predictors after preselection were used for model fitting and further predictor selection. The remaining predictor numbers after preselection for each roadkill sample are: Multispecies, 31 predictors; *B. bankorensis*, 14 predictors; *B. robusta*, 10 predictors; *H. latouchii*, 16 predictors; *O. swinhoana*, 16 predictors; *R. sauteri*, 10 predictors; *B. robusta* April, 8 predictors; *B. robusta* May, 19 predictors; *B. robusta* June, 9 predictors; and *B. robusta* July–October, 7 predictors (Suppl. material 1: table S3).

Modeling and predictor selection

Predictor selection was carried out through random forest (RF) and logistic regression (LR) binary classification model fitting. RF was selected for its ability to capture non-linear interactions, while LR provides interpretable linear relationships (Couronné et al. 2018; Chen and Chen 2020). To remove scale bias in importance rankings, all predictors were standardized before model fitting. To account for varying sample sizes and ensure balanced evaluation across datasets, stratified train–test splits were tailored to each sample (Norberg et al. 2019). All samples were severely imbalanced except for the multispecies sample (Suppl. material 1: fig. S3). The splitting ratio was adjusted to retain meaningful test sets for model fitting according to respective sample sizes (Valavi et al. 2021; Sillero et al. 2023) (Suppl. material 1: table S4). Models were trained with two-fold cross-validation, repeated five times to ensure stability.

Class imbalance was addressed during model training. In random forest models, class imbalance was addressed by using the Random Over-Sampling Examples (ROSE) method (Lunardon et al. 2014; Muchlinski et al. 2016; Mizuno et al. 2024). ROSE generates synthetic minority-class samples via a smoothed bootstrap approach, which addresses both class imbalance and the spatial sampling bias inherent in our citizen science data (Lunardon et al. 2014). In logistic regression, class imbalance was addressed with class weighting (Maalouf et al. 2018), which addresses class imbalance but does not directly correct the underlying sampling bias. Given limited prior knowledge of our study species' responses to roadkill environmental factors—a limitation that could bias single-model outcomes (Li et al. 2017)—we considered only predictors retained by both models as consensus predictors (Kapoor et al. 2024). The consensus results also ensure results are consistent across both modeling strategies, which are less likely to be spurious artifacts of one particular modeling or correction technique and more likely to reflect true ecological signals resilient to different treatments of data bias.

We applied stepwise selection to reduce predictor numbers and minimize overfitting, using the absolute difference between training and test AUC (AUC. diff) as the criterion. This was calculated across 1,000 fitted replicate models. To enhance generalization and ensure robust ecological interpretations, we prioritized predictors that minimized this value. Because AUC can appear favorable despite low precision in severely imbalanced datasets, we used AUPRC, which prioritizes minimizing false positives, as a secondary measure for a more conservative model reliability assessment (McDermott et al. 2024).

Final selected predictors were assessed for variable importance using permutation importance from RF and absolute t-statistics from LR (Fisher et al. 2019). Predictor interactions were evaluated with Friedman's H-statistic, and partial dependence plots (PDPs) were generated to visualize influences on roadkill probability, averaged across 1,000 replicates (Oh 2019; Greenwell 2024).

All analyses were conducted in R 4.3.2 (R Core Team 2023) using the following packages: caret 6.0–94 (Kuhn 2008), randomForest 4.7–1.2 (Liaw and Wiener 2002), ROSE 0.0–4 (Lunardon et al. 2014), harmonicmeanp 3.0.1 (Wilson 2019), spatialRF 1.1.4 (Benito 2022) for VIF, ROCR 1.0–11 (Sing et al. 2005) for AUC and AUPRC, pdp 0.8.1 (Greenwell 2017) for PDPs, and iml 0.11.1 (Molnar et al. 2018) for feature interaction.

Results

Consensus roadkill environmental predictors

A consensus analysis between RF and LR models yielded 24 robust predictors, equally split into 12 habitat-related and 12 road-related variables (Table 2). Their relationships with roadkill probability were examined using PDPs (Suppl. material 1: figs S4–S12). Across one multispecies, four single-species, and five temporal single-species models, each model generally produced a distinct set of consensus predictors (Suppl. material 1: tables S5, S6), indicating different species are influenced by distinct environmental factors. No consensus predictors were identified for the *H. latouchii* model. Among all predictor categories, no topographic predictor was retained across models.

Table 2. Consensus predictors by category. The Table shows predictors' relationship (Effect) to roadkill probability based on PDPs (Figs. S3–S11). Symbols: (+) positive, (−) negative, (0) flat or fluctuating; 0/− and 0/+ indicate differing effects between RF and LR. A positive relationship indicates that higher predictor values (e.g., length, width, distance, area) correspond to higher predicted roadkill probability. Conversely, a negative relationship indicates that lower predictor values (e.g., shorter distances to rivers) correspond to higher probability.

Predictor	Sample	Effect	Abreviation
Habitat-related			
Water Features			
River area	*Odorrana swinhoana*	+	River_dw050
Distance to Ruii Creek	*Buergeria robusta* May	-	D_Ruizi
Distance to stream crossing	*Odorrana swinhoana*	-	D_StreamCr
Distance to uphill stream	*Bufo bankorensis*	0/-	D_StreamUp
Distance to water source	*Buergeria robusta* June	-	D_WaterSo
Maximum Strahler order (50 m downhill)	Multispecies (Anuran)	+	Stramax_dw050
Maximum Strahler order (25 m uphill)	*Odorrana swinhoana*	-	Stramax_up025
Landscape Features			
Bamboo forest area (200 m downhill)	*Buergeria robusta* June	-	BambF_dw200
Broadleaf forest area (25 m uphill)	*Odorrana swinhoana*	+	BLeafF_up025
Crop land area (25 m downhill)	*Buergeria robusta*	+	Crop_dw025
Orchard area (150 m uphill)	*Buergeria robusta* April	-	Orchard_up150
Housing area (150 m downhill)	*Buergeria robusta* May	-	House_dw150
Road-related			
Streetlights			
Number of streetlights (50 m downhill)	*Buergeria robusta* May	-	Light_dw050
	Rana sauteri	+	
Number of streetlights (150 m downhill)	*Bufo bankorensis*	0/+	Light_dw150
	Rana sauteri	+	
Number of streetlights (150 m uphill)	*Buergeria robusta* June	+	Light_up150
Number of streetlights (25 m along the road)	*Rana sauteri*	+	RS_light
Roadside Land Uses and Covers			
Length of road junction (25 m along the road)	*Buergeria robusta*	-	RS_RoadJunc
Length of unpaved open ground (25 m along the road)	*Buergeria robusta* April	+	RS_OpenGV
Vertical Structures			
Length of Jersey barrier	*Bufo bankorensis*	-	RS_JerseyB
Length of W-Beam guardrail	*Buergeria robusta* July-Oct	+	RS_WBeam
Length of uphill concrete retaining wall, < 4 m H (25 m along the road)	*Buergeria robusta*	-	RS_CRW
Length of downhill concrete retaining wall, < 4 m H (25 m along the road)	*Buergeria robusta* June	+	RS_CRWdw
Open Drainage Channels			
Length of open drainage channel with vegetation (25 m along the road)	*Bufo bankorensis*	+	RS_OpDrainG
Length of Open drainage channel waterlogged (25 m along the road)	*Bufo bankorensis*	-	RS_OpDrainW

Among all consensus predictors, water features form the most consistent and significant group. Maximum stream order within 50 m downhill (Stramax_dw050) is the only consensus predictor of the multispecies models, indicating that the overall effect of water feature influences within a stream network context on a community level. Shorter distances to water features of different water sources are associated with higher roadkill probability for *B. bankorensis*, *O. swinhoana*, and *B. robusta* May and June models. Landscape features also contributed, particularly to *B. robusta* and its temporal models. Natural broadleaf forest influenced the consensus predictors for *O. swinhoana*, whereas bamboo forest, cropland, orchard, and residential land uses were influential in the *B. robusta* models.

Among road-related predictors, streetlights are the most common consensus predictors, appearing in four of the nine single-species and temporal models (*B. bankorensis*, *B. robusta* in May and June, and *R. sauteri*). Two of these predictors were the only ones retained in more than one model across all consensus predictors. Streetlights were positively associated with roadkill probability at most effective scales, meaning that roadkill probability increased with increasing light density. Of particular interest, the 50 m downhill predictor was positively associated with *R. sauteri* but negatively associated with the *B. robusta* May model, indicating that higher streetlight density at this close range corresponded to lower roadkill probability for *B. robusta* during this period. In contrast, the *B. robusta* June model was positively associated with the 150 m uphill streetlight scale. The 150 m downhill scale was relevant for *B. bankorensis*, although the two algorithms showed slightly different patterns. In the RF model, roadkill probability increased mainly at higher streetlight densities, whereas in the LR model the positive relationship was consistent across the full range of values. Overall, these patterns show that the influence of streetlights is sensitive to buffer scale, direction relative to the road, and species ecology, and that roadkill risk can shift over time even within the same species.

The remaining predictor groups, namely roadside land-use and land-cover, vertical structures, and open drainage channels, were exclusive to only two species. The first group was retained only in the *B. robusta* models and showed opposing relationships across subsets and predictors. The second group was also predominantly linked to *B. robusta*, with three of four predictors retained for this species and one for *B. bankorensis*, again with contrasting associations. *B. robusta* and its June subset in particular showed different associations with uphill and downhill retaining walls. Open drainage channels were exclusive to *B. bankorensis* and similarly exhibited opposing relationships. Together, these patterns indicate that different roadside features have species-specific functional effects and that these effects can vary seasonally, even within the same species.

Model performance evaluation

Model reliability was assessed using mean absolute AUC difference (AUC.diff) across 1000 replicates (Suppl. material 1: table S7). At the multispecies level, AUC.diff was low for both RF (0.028) and LR (0.004). For single-species models, values ranged from 0.003–0.012 for RF and 0.008–0.022 for LR, except for *R. sauteri* where LR showed higher overfitting (0.054). Temporal models of *B. robusta* (April–October) consistently had low AUC.diff for both RF (0.004–0.012) and LR (0.003–0.015). Across all models, 95% confidence intervals were narrow (0.004–0.012).

Model discrimination was evaluated with AUC and AUPRC. At the multispecies level, RF and LR achieved test AUCs of 0.552–0.610. Single-species AUCs were higher (0.746–0.827), except for *B. robusta* (0.660–0.673). However, temporal models of *B. robusta* performed substantially better (0.780–0.851). AUPRC values exceeded baseline in all cases. The multispecies model yielded AUPRCs of 0.552–0.593 (1.1–1.2 × baseline). Single-species models performed better: *B. robusta* reached 0.352–0.369 (2.1–2.3 × baseline), *R. sauteri* 0.316–0.485 (12.6–19.4 × baseline), and other species 0.301–0.358 (3.6–5.9 × baseline). Temporal models of *B. robusta* achieved higher performance values: 0.322–0.412 (4.8–12.5 × baseline).

Discussion

This study shows that species-specific, temporal, and multiscale analyses are essential for understanding how species traits, hydrological connectivity, landscape configuration, and seasonal behavior interact to shape amphibian roadkill. Using detailed field surveys and a dual-model consensus framework, we identified nuanced driver–response relationships that generalized models could not detect. Multispecies models revealed broad patterns, but single-species and temporal models offered far greater precision. Across samples, consistent predictor groups emerged, including water features, landscape composition, and fine-scale site features such as streetlights, junctions, retaining walls, and drainage channels indicating shared ecological responses that support broader generalization. The 24 consensus predictors, evenly divided between habitat- and road-related factors, highlight the equal importance of both broad landscape attributes and understudied roadside structures in shaping roadkill risk. These patterns reveal two key insights: fine-scale site features can influence mortality as strongly as habitat context, and there are clear inter- and intra-species variations in responses to roadkill drivers, shaped by species behavior and life-cycle traits (Huang et al. 2004). By assessing predictor selections against established amphibian ecology literature, we ensured that these outcomes are biologically meaningful rather than correlational artifacts (Semlitsch 2008). Together, these findings strengthen the mechanistic foundation needed for planning and design interventions that support sustainable development (Forman and Alexander 1998; van der Ree et al. 2015).

Consensus roadkill environmental predictors

Water-related predictors consistently emerged as the strongest contributors to amphibian roadkill patterns. Larger river area and stream order, or short distances to streams, rivers, and roadside water sources generally showed stronger associations with roadkill probability. These patterns reflect amphibians' dependence on aquatic habitats that guide movement (Santos et al. 2007; Pinto et al. 2023). Directionality was important: downhill water features tended to align with higher roadkill probabilities, whereas high-quality uphill streams showed negative associations, suggesting fewer crossings when suitable habitat is available upslope. These mechanisms were evident in species-specific responses. For *O. swinhoana*, proximity to downhill rivers was positively associated with roadkill probability, whereas larger uphill streams and greater distances from stream crossings showed negative associations, consistent with its use

of shaded hillside habitats (IUCN 2020c). For *B. robusta*, peak-breeding roadkill probability was positively associated with proximity to downhill creeks and roadside water sources, underscoring the role of riparian connectivity in structuring the seasonal movements of this stream breading species that inhabits hilly broad-leaved forests (IUCN 2019).

Landscape predictors also influenced roadkill patterns. Uphill broadleaf forests increased risk for *O. swinhoana*, reflecting its forest-dwelling ecology (IUCN 2020c). In contrast, downhill cropland increased mortality for *B. robusta*, consistent with its vulnerability in agricultural landscapes (IUCN 2019), which are scattered along our study road. Negative associations with bamboo, orchards, and residential areas during April–June suggest seasonal habitat shifts and possible source–sink dynamics across fragmented landscapes (Pulliam 1988). Notably, other amphibians' roadkill, such as urodeles, has also been linked to low housing density (Matos et al. 2012).

Streetlight density showed positive associations with roadkill probability at all scales, consistent with anurans' nocturnal foraging near artificial lights (Coelho et al. 2012; Van Grunsven et al. 2017). A critical finding was the contrasting species responses: *B. robusta* in May showed a negative association at finer streetlight scales (Light_dw050), whereas *R. sauteri* exhibited a positive association. For *B. robusta*, which forages extensively in downhill areas between the road and the river during the peak of its breeding season (March–August; Huang et al. 2001), higher streetlight density may elevate ambient light levels in these zones, reducing the need to approach the road and allowing individuals to remain near the water. These divergent responses indicate that illumination effects are species- and season-specific, reinforcing that mitigation cannot be uniformly generalized across species or taxa. For *R. sauteri* in particular, three illumination predictors were retained, suggesting that artificial lighting may influence the spatial concentration of mass-migration crossings, an effect not previously documented and highly relevant for mitigation planning.

Road junctions and unpaved open areas were also associated with roadkill, likely reflecting movement corridors and habitat preferences (Coelho et al. 2012; van der Ree et al. 2015). Negative association with junctions for *B. robusta* may reflect faster carcass removal or long-term population declines at these sites (Matos et al. 2012). Vertical structures showed contrasting effects; Jersey barriers and uphill retaining walls under 4 m (RS_CRW) reduced roadkill, consistent with findings for *Bufo bufo* in Portugal (Matos et al. 2012). These long structures likely limit road access, whereas shorter structures may create fence-end effects similar to drift fences (Helldin and Petrovan 2019). In contrast, long downhill retaining walls (RS_CRWdw) and W-Beam guardrails increased mortality, either by trapping amphibians or allowing access through gaps. For example, *B. robusta* moving downhill toward rivers during its breeding peak in June (Huang et al. 2001) may be trapped by retaining walls, while W-Beam guardrails may permit crossing and collisions during post-breeding return migrations in July-October. Species traits such as the large body size of *B. bankorensis* and climbing ability of the arboreal *B. robusta* likely shape these outcomes (Chang et al. 2011; IUCN 2019; IUCN 2020a).

Drainage channels also had dual roles. Vegetated channels acted as ecological traps, while longer waterlogged channels served as barriers, preventing road crossings. This pattern aligns with Matos et al. (2012), who found that

shorter waterlogged ditches were associated with higher *B. bufo* roadkill. Longer channels may be wider, deeper, and more slippery, reducing crossings by large amphibians such as *B. bankorensis* (Chang et al. 2011; Helldin and Petrovan 2019). These findings emphasize the importance of specific structural designs in shaping roadkill outcomes.

Predictors with limited consensus and methodological implications

A fuller understanding of the results requires acknowledging cases where predictors or model types showed limited consensus, as these reveal the ecological and methodological conditions shaping model performance. The multispecies model retained only one consensus predictor, maximum stream order within 50 m downhill, consistent with studies linking anuran roadkill to waterbody proximity (Coelho et al. 2012; Pinto et al. 2023; Jones et al. 2024). This reinforces the ecological importance of water features and the value of group-level analyses for identifying shared risk factors, even when species respond differently. Multispecies models also remain useful when species-level carcass identification is limited (Coelho et al. 2012). For *H. latouchii*, the absence of consensus predictors likely reflects its sedentary, non-migratory ecology, broad habitat use including forest, stream, or irrigated systems (IUCN 2020b), and the small sample size available for modeling. Methodological differences between Random Forest and Logistic Regression, particularly RF's ability to capture complex interactions versus LR's linear structure, further contributed to inconsistent predictor retention (Couronné et al. 2018).

No topographic predictors reached consensus, contrasting with studies where elevation influenced amphibian roadkill (Matos et al. 2012), but this is consistent with the limited topographic variation in our study area, which likely reduced explanatory power (Lei et al. 2023). Discrepancies between LR and RF were rare, occurring for only two predictors in one species model, involving distance to uphill streams and streetlight density for *B. bankorensis*. This limited divergence underscores both the complexity of roadside environments and the overall robustness of the consensus approach. Notably, structural predictors such as Jersey barriers and drainage channels were consistently retained for this species, suggesting that movement may be constrained by body size and behavior, similar to patterns reported for other large toads such as *B. bufo* (Matos et al. 2012).

Model performance

The dual-model consensus approach combining RF and LR provided a robust basis for selecting ecologically meaningful predictors, as retaining only variables identified by both algorithms increased confidence in their relevance. Low AUC.diff values indicated minimal overfitting and strong generalizability (Nakagawa and Cuthill 2007; Valavi et al. 2021). Single-species and temporal models outperformed multispecies models, reflecting the limitations of aggregating taxa with differing ecologies. Our result is also consistent with previous studies showing that sympatric and conspecific species can differ in life cycles and behaviors (Huang et al. 2004). Temporal models of *B. robusta* were particularly strong (AUC up to 0.851), revealing distinct predictors across

pre-breeding, breeding, and post-breeding periods. These patterns highlight the importance of temporal resolution for ecological planning and show that static, year-round hotspot maps may overlook critical seasonal dynamics (Jarvis et al. 2019; Lin et al. 2019).

Implications for ecological planning and sustainable development

Although the mitigation recommendations reflect the specific species and landscape context of the study road, they demonstrate how the framework translates ecological evidence into practical planning and design guidance. Because mitigation measures are derived primarily from predictor-group patterns, species-specific interpretations are used to refine rather than drive the recommended actions. The core principles, which relate predictors to effective scales, identify structural barriers, guide light management, and maintain hydrological connectivity, are broadly transferable despite regional variation in threshold distances or design parameters. Effective scales indicate where interventions are most likely to work, so the measures presented here should be viewed as examples rather than universal prescriptions. Table 3 summarizes the framework, with full specifications provided in the Suppl. material 1: table S8.

Planning stage: avoidance and strategic placement

To translate the above findings into practical guidance, we present mitigation interventions aligned with the identified predictors and their effective scales. Since avoidance is consistently identified as the most effective form of mitigation (van der Ree et al. 2015), planning should prioritize routing alignments away from critical habitats and, for example, maintaining buffers of at least 50 m from rivers and large downhill streams, and 25 m from uphill broadleaf forests. Land-use regulations should also restrict new agricultural or residential developments in high-risk zones adjacent to roads. Where avoidance is not feasible or at existing roads, the planning stage is the most cost-effective time to locate permanent mitigation structures to avoid retrofitting cost (Patrick et al. 2010; Gunson et al. 2016). Underpasses with drift fences should be prioritized in high-risk segments identified by hotspot modeling (Karanasios et al. 2021), particularly near stream crossings and uphill streams, and in areas where roads intersect key habitats (Patrick et al. 2010; van der Ree et al. 2015; Hamer et al. 2023). Habitat compensation can also be considered through the construction of waterbodies (e.g., marshlands, ponds) outside the effective scales to offset habitat loss (van der Ree et al. 2015).

Design stage: ecological engineering

At the design stage, infrastructure can be engineered to be more permeable and less lethal. For streetlights, this involves more than simple presence or absence. Design should incorporate amphibian-friendly solutions such as spectral adjustment (e.g. amber or red light), shielding to reduce light spill into adjacent habitats, and seasonal scheduling to dim or switch off lights during peak migration periods (Van Grunsven et al. 2017). Vertical structures, including retaining walls and barriers, should be designed or retrofitted to avoid trapping

Table 3. Strategic mitigation framework (overview). Summary of predictors, their effective scales of influence, roadkill associations, and representative mitigation measures by application stage. The full set of measures, guidelines, technical specifications, and stakeholder responsibilities are provided in Suppl. material 1: table S8.

Predictors	Effective Scale(s)	Roadkill Association	Mitigation	Abreviation
Planning Stage				
Rivers and Large streams	50 m downhill	Higher risk near or at larger waterbodies	• Avoid alignment • Drift-fenced underpasses * if unavoidable • Habitat compensation	River_dw050
				Stramax_dw050
				D_Ruizi
Large streams	25 m uphill	Higher risk near smaller waterbodies		Stramax_up025
Uphill streams	Near distances	Mixed effects		D_StreamUp
Stream crossings	Near crossings	Higher risk near crossings		D_StreamCr
Broadleaf forest	25 m uphill	Higher risk at larger patches		BLeafF_up025
Bamboo forest	200 m downhill	Higher risk at smaller patches	• Avoid alignment • Protect as buffer habitat • Habitat compensation	BambF_dw200
Agriculture & Residential	25–150 m around road	Mixed seasonal effects	• Restrict developments near roads • Habitat compensation	Crop_dw025
				Orchard_up150
				House_dw150
Streetlights (planning)	150 m up/down	Species- and season-dependent risk	• Avoid placement near sensitive habitats • Reduce spacing	Light_dw050
				Light_dw150
				Light_up150
				RS_light
Design Stage				
Streetlights (design)	150 m up/down	Light-induced mortality risk	• Adjust spectra • Shielding • Fixture redesign • Seasonal scheduling	Light_dw050
				Light_dw150
				Light_up150
				RS_light
Road junctions	Junction's width	Higher risk at smaller junctions	• Drift-fenced underpasses	RS_RoadJunc
Vertical structures (Barriers & retaining walls)	Along road (up/down)	Mixed seasonal and barrier effects	• Redesign/retrofit with permeability and guiding features • Drift-fenced underpasses *	RS_JerseyB
				RS_WBeam
				RS_CRW
				RS_CRWdw
Drainage channels (design)	Along road	Trap risk	• Engineer with escape routes • Adapt geometry to avoid trapping	RS_OpDrainG
				RS_OpDrainW
Temporary Measures				
Migration hotspots	High-risk segments during peak periods	Mass mortality during migrations	• Dynamic signage • Temporary speed reduction • Road closures	
Temporary fencing	High-risk migration zones	Short-term barrier	• Deploy fences and bucket traps seasonally	
Operation & Maintenance Stage				
Unpaved open grounds	Along road	Amphibian movement corridors	• Vegetation management (mowing, litter removal)	RS_OpenGV
Underpasses & drift fences (maintenance)	Installed sites	Barrier if degraded	• Regular inspection and cleaning	
Drainage channels (maintenance)	Along road	Trap risk if clogged	• Regular cleaning to maintain function	RS_OpDrainG
				RS_OpDrainW
Streetlights (management)	150 m up/down	Light disturbance if unmanaged	• Monitor and adjust scheduling/ intensity	All types
Water sources (roadside)	Local leakage near road	Attract amphibians	• Inspect leaks/irrigation • Awareness programs	D_WaterSo

* Design spacing, dimensions, and fence length to species-specific needs. Note: The detailed mitigation strategy is presented in Suppl. material 1: table S8.

and to allow permeability, for example by incorporating escape ramps, guiding elements or permeable sections, especially where they intersect known movement corridors (Chang et al. 2011). Drainage channels, which can act as traps, should be designed with sloped sides or escape routes to allow animals to exit (Jarvis et al. 2019). Where underpasses with drift fences are installed, their dimensions, spacing and fence length should follow species-specific recommendations (Patrick et al. 2010; Gunson et al. 2016; Helldin and Petrovan 2019).

Temporal measures

For predictors with strong seasonal effects, timing-based interventions are critical. During predictable mass migration events (e.g., for *B. robusta* and *R. sauteri*), temporary measures including dynamic signage, speed reductions and short-term road closures at key hotspots can substantially reduce mortality (van der Ree et al. 2015). In parallel, temporary fencing and bucket-trapping systems led by community volunteers or NGOs can provide short-term mitigation where permanent structures are absent (Patrick et al. 2010). Education campaigns can complement these measures by raising driver awareness and fostering community involvement in conservation efforts (van der Ree et al. 2015).

Operation and maintenance

Effective mitigation requires ongoing management. Road agencies must ensure that permanent structures such as underpasses and drift fences are regularly inspected and maintained to remain functional (Hamer et al. 2023; van der Ree et al. 2015). Drainage channels should be kept clear of debris so that they do not function as unintentional physical or ecological traps for amphibians (Laurance et al. 2009). For streetlights, operational management includes adjusting seasonal schedules or dimming intensity to align with amphibian activity periods. Water agencies and local authorities should inspect irrigation systems or other leakage sources near roads (D_WaterSo) and promote public awareness programmes to reduce unintended water attraction for amphibians (van der Ree et al. 2015). The strategic overview in Table 3 summarises predictors, their effective scales and representative mitigation measures by application stage, with the full set of measures, guidelines and technical specifications provided in Suppl. material 1: table S8.

Limitations and opportunities

This study also highlights limitations that create opportunities for refinement. Although spatially detailed, the datasets were temporally limited, reducing our ability to capture interannual dynamics and full seasonal variation. Long-term monitoring, supported by fine-scale surveys, would strengthen temporal analyses and improve multispecies modeling. Expanding citizen science participation remains important, as shown by the detection of streetlight-related predictors for *R. sauteri* during brief migration events. More detailed assessments of drainage channels, culverts, and their functional states would enhance mechanistic understanding of roadkill processes and inform future design improvements. Incorporating dynamic environmental variables such

as rainfall, temperature, traffic, road width, and finer-scale topography would also increase model realism. Further, the adoption of ensemble-based approaches could possibly reduce model discrepancies (Lin et al. 2019). Such advances will support more effective mitigation and the designs of safe wildlife crossings (Gunson et al. 2016). Addressing these limitations will not only improve predictor interpretability but also expand opportunities for applying the framework to other taxa and uses as shown next.

Methodological contributions and framework transferability

Across species, predictor groups showed consistent patterns grounded in shared ecological mechanisms. Water features shaped risk as downhill streams channel movements toward roads, while high-quality uphill streams reduce crossings. Landscape features influenced habitat quality and seasonal movement. Streetlights affected nocturnal activity, roadside land uses modified microhabitats, while vertical structures and drainage channels altered permeability or created trapping conditions. These mechanisms explain framework generalizability across regions. However, contrasting responses among *B. robusta*, *O. swinhoana*, and *R. sauteri* indicate that species ecology and seasonality must guide local mitigation design.

A key contribution of this study lies in its methodological approach. Multiscale uphill-downhill buffer approach, which captured habitat and movement asymmetries. The predictor preselection pipeline enhanced ecological interpretability while reducing statistical redundancy (Wilson 2019; Aranda-Michel et al. 2022). The dual Random Forest–Logistic Regression consensus approach identified predictors consistently supported across model structures, reducing algorithmic bias (Couronné et al. 2018; Kapoor et al. 2024). Performance metrics supported model reliability (Valavi et al. 2021; McDermott et al. 2024). Integrating citizen science captured rare events (Cosentino et al. 2014), while fine-scale surveys resolved movement mechanisms beyond coarse predictors.

The framework is broadly scalable and transferable because it focuses on mechanisms rather than species labels. Although some predictor values, effective distances and species responses reflect the specific hydrological, topographic and structural context of our road system, several components are broadly generalizable. Directional hydrology, roadside structural permeability, landscape composition and illumination effects operate through widely shared mechanisms. In contrast, traits such as breeding phenology, movement timing and microhabitat preferences limit generalization and determine which measures require local adaptation. Clarifying these region-specific and transferable components strengthens the framework's applicability beyond the Sanxia system. Although predictor values are context-specific, the methodological workflow (Fig. 3) applies widely to linear features including roads, railways, canals, energy corridors or other borders and adapts to varied environments from arid to subtropical systems with dense anthropogenic use. The framework can extend to human safety contexts (Thakur et al. 2025) and public-space design considerations such as pedestrian risk mapping and roadside design evaluation. Its emphasis on interactions between environmental patterns and structural conditions aligns with sustainable development goals and underscores broader planning relevance.

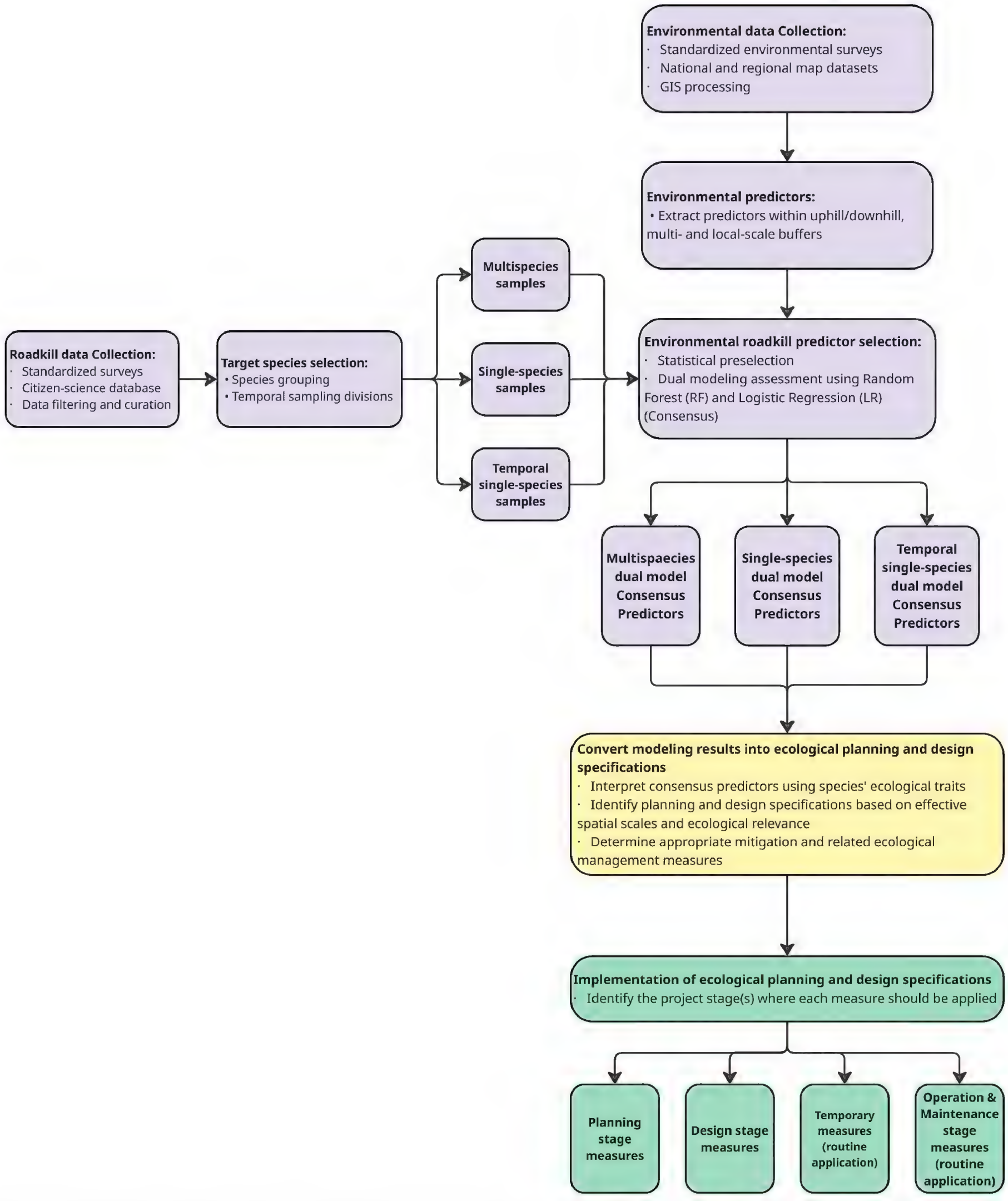
Environmental data Collection:
· Standardized environmental surveys
· National and regional map datasets
· GIS processing
Environmental predictors:
• Extract predictors within uphill/downhill, multi- and local-scale buffers
Roadkill data Collection:
· Standardized surveys
· Citizen-science database
· Data filtering and curation
Target species selection:
• Species grouping
• Temporal sampling divisions
Multispecies samples
Single-species samples
Temporal single-species samples
Environmental roadkill predictor selection:
· Statistical preselection
· Dual modeling assessment using Random Forest (RF) and Logistic Regression (LR) (Consensus)
Multispaecies dual model Consensus Predictors
Single-species dual model Consensus Predictors
Temporal single-species dual model Consensus Predictors
Convert modeling results into ecological planning and design specifications
· Interpret consensus predictors using species' ecological traits
· Identify planning and design specifications based on effective spatial scales and ecological relevance
· Determine appropriate mitigation and related ecological management measures
Implementation of ecological planning and design specifications
· Identify the project stage(s) where each measure should be applied
Planning stage measures
Design stage measures
Temporary measures (routine application)
Operation & Maintenance stage measures (routine application)

Figure 3. Strategic Ecological Planning, Design, and Implementation Framework. This workflow summarizes the complete process used to identify environmental predictors of roadkill risk and translate modeling outputs into actionable insights for ecological planning, design, and project implementation toward sustainable development. The purple phase represents the methodological foundation, including roadkill and environmental data collection, extraction of predictors across local and multiscale buffers, and robust consensus-based predictor selection from dual modeling approaches. The yellow phase represents the translation of these predictor sets into planning and design specifications by integrating species' ecological traits, effective spatial scales, and ecological relevance, while also determining appropriate mitigation and related ecological management measures. The green phase represents implementation, where identified measures are assigned to the appropriate project stages, including planning, design, temporary application, and operation and maintenance, supporting sustainable ecological management at effective spatial scales that extend beyond the narrow boundaries of road infrastructure toward sustainable development.

Conclusions

This study identified the complex, multiscale environmental drivers of amphibian roadkill by integrating multispecies, species-specific, and temporal analyses. Our dual-model consensus approach showed that fine-scale roadside features, such as streetlights and drainage channels, can be as influential as broad-scale habitat variables like forests and rivers. The strong performance of species-specific and temporal models confirms that roadkill risk varies with species ecology and life-cycle events, including breeding migrations.

The primary contribution of this work is a transferable methodological framework that links ecological evidence with practical application. Moving beyond hotspot identification, we provide a blueprint for translating ecological data into evidence-based guidelines. The uphill–downhill buffer design and consensus-based modelling offer reliable tools for identifying meaningful predictors and reducing model-dependent bias.

Our findings inform a hierarchical mitigation strategy across planning, design, and operational stages. Key measures include avoiding critical habitats, habitat compensations, engineering design facilitating animal movement (e.g., friendly lighting, modified retaining walls), and applying temporal actions such as dynamic signage, temporary fences, or local government involvement in coordinating rescue efforts. This framework supports the design of landscapes that are more compatible with species conservation and sustainable development.

Future research should pursue long-term monitoring to capture inter-annual variability and strengthen predictions. Incorporating dynamic variables such as rainfall and traffic volume, alongside higher-resolution topography, would refine understanding of roadkill mechanisms. We also recommend extending this framework to other taxa and conducting behavioral studies to validate species-specific responses. In addition, the framework can be applied to human use considerations to support the design of safe and ecologically sound public spaces.

Overall, this research shows that detailed ecological analysis is essential for effective conservation. By linking species traits, environmental drivers, and practical interventions, we can move toward development that integrates biodiversity conservation into sustainable planning.

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Additional information

Conflict of interest

The authors have declared that no competing interests exist.

Ethical statement

No ethical statement was reported.

Use of AI

During the preparation of this work the author Panagiotis I. Karanasios used ChatGPT, Skywork, Grok, editGPT, and DeepSeek in order to paraphrase and improve English writing. After using these tools, the author reviewed and edited the content as needed and takes full responsibility for the content of the publication.

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Author contributions

Panagiotis I. Karanasios: Conceptualization, Investigation, Data curation, Methodology, Writing—Original draft preparation, Writing—Review and editing. Dirk S. Schmeller: Methodology, Writing—Review and editing. Zong-Ting Hsu: Investigation, Data curation. Yu-Pin Lin: Conceptualization, Methodology, Writing—Review and editing, Supervision.

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Data availability

The datasets analyzed, including survey data, citizen science data, and random sample data, are publicly available in a Zenodo repository https://www.doi.org/10.5281/zenodo.17918557. The code supporting the findings of this study are openly available in the GitHub repository at https://github.com/pankagit/code_amphi.git.

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Supplementary material 1

Supplementary tables and images

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Data type: docx

Explanation note: Supplementary tables and images arranged in the main text appearance order.

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